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Modeling coastal land and housing markets: Understanding the competing influences of amenities and storm risks

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ABSTRACT

The costs from coastal storms and hurricanes are expected to increase with climate change yet populations in coastal areas continue to grow. In this paper, we develop a dynamic spatial simulation model of coastal land and housing markets and study the competing influences of storm risks and amenities. The model is parameterized to the Mid-Atlantic region of the United States, where hurricanes occur relatively infrequently, and then used to assess how spatial patterns of development would change if storm frequency increases. Results show that spatial patterns change very little—approximately 45 percent of the land area in the coastal region is developed by the final model period in both the baseline and high storm risk scenarios and the coast sees more development than inland areas in all scenarios. The countervailing coastal amenity matters more with the percent developed in the coastal region varying between 29 and 51 percent depending on the scenario. Perhaps more importantly, we find that heterogeneous households sort differently on the landscape in our different scenarios. When storms are more frequent, average land prices near the coast are 1.2–11.8 percent lower, which leads to households with lower average incomes locating there. The results highlight the difficulty policymakers may have in altering private land and housing market outcomes to reduce storm costs in coastal regions.

1. Introduction

The economic costs of extreme weather events have been rising in the United States and around the world (Benson and Clay, 2004; Gall et al., 2011; Kousky, 2013). There is some debate about the reasons for the increase, but most studies agree that the primary driver is an increase in exposure—that is, more people and properties, and more valuable properties, located in harm's way (Pielke and Downton, 2000; Pielke et al., 2008; Bouwer, 2011; Hallegatte et al., 2013). Moreover, these trends are expected to continue in the future. Hallegatte et al. (2013) estimates that population and Gross Domestic Product (GDP) growth alone will increase average annual flood losses in the 136 largest coastal cities in the world from $6 billion to $52 billion by 2050, with climate change leading to even larger losses.

According to the United Nations Atlas of the Ocean, 44 percent of the world's population lives within 150 km of the coast, which is more than the total number of people on earth in 1950 (United Nations, 2011). The National Oceanic and Atmospheric Administration (NOAA), estimates that 39 percent of the U.S. population lives in coastal shoreline counties, which account for only 10 percent of U.S. land area (NOAA, 2013). The population density of these counties increased by 28 percent between 1970 and 2010, and NOAA predicts the number will be an additional 6.5 percent higher in 2020 (NOAA, 2013). If climate change leads to an increase in the frequency of the most severe coastal storms, which is the current projection for the U.S. Atlantic coast (Kossin et al., 2017; Emanuel, 2013), and sea level rise exacerbates the impacts of those storms through worsening storm surge flooding, as most scientists predict (Slangen et al., 2014; Lin et al., 2012), the economic costs of disasters will increase in the future.

In order to design effective policies to reduce those costs, one needs to understand the factors that explain the dynamics of coastal development. Why does population continue to grow in coastal areas when those areas are the most at risk from weather-related disasters? This is the question we explore in this paper. Specifically, we analyze two of the competing influences that exist in coastal areas: the pull of coastal amenities and the push of expected costs due to storms and hurricanes. Using a dynamic spatial simulation model of housing and land markets, we assess how these two factors affect spatial patterns of development and the evolution of land and house prices in a coastal region over time. We conduct two simulation exercises. First, we assess how higher storm risks, all else equal, might affect the location choices of households and resulting land and house prices compared to a baseline climate

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scenario. We then carry out sensitivity analyses on the coastal amenity—specifically, we assess how different coastal amenities affect land use outcomes, holding all else equal.

The model is an economic agent based model (ABM) with three types of agents: landowners, a real estate developer, and housing consumers. The ABM incorporates substantial heterogeneity in agents and is able to analyze both the dynamic and spatial patterns of development (Irwin, 2010; Iftekhar and Tisdell, 2015). The stylized setting abstracts from many other complicating real-world factors that can make interpreting results difficult and allows us to isolate the individual effects of amenities and storm risks (Felsenstein and Lichter, 2014).

In the model, landowners decide each period whether to sell their land to the developer; the developer buys land and builds houses to satisfy consumer demand; and consumers that are heterogeneous in income and preferences choose housing, which is characterized by lot size, house size, and location. In making their choices, consumers maximize utility subject to a budget constraint, and their utility depends partially on house location—i.e., houses located closer to the coast have a higher embodied coastal amenity value. At the same time, there is also an expected cost associated with locations closer to the coast: the property damage caused by coastal storms and hurricanes. We intentionally abstract from considerations of insurance markets and storm mitigation activities (such as installation of hurricane straps and shutters or house elevation). We also assume housing consumers understand the expected costs associated with coastal storms at each possible location on the landscape and fully internalize those expected costs in their decision-making.[1] Our objective is to remove these complicating factors and analyze what the market outcomes would look like if fully informed and rational consumers make tradeoffs of amenities and risks in their location decisions. Policymakers, the general public, and some academic studies point to failures in the market for flood insurance (Michel-Kerjan 2010; Michel-Kerjan and Kunreuther, 2011), a lack of good understanding about storm risks (Botzen et al., 2015), and decisionmaking based on heuristics and other behavioral rules other than utility maximization (Dillon et al., 2011; Meyer et al., 2014) as reasons for the continual rise in costs from coastal storms. This paper explores whether it is simply the appeal of coastal amenities – e.g., recreation access, aesthetics and views – that outweighs expected storm costs.

The model is parameterized to the Mid-Atlantic region of the U.S., including to Mid-Atlantic storm frequencies and damages from major storms in the region, and then used to assess how development patterns and land and housing prices change if the storm frequency increases to levels in other parts of the U.S. The annual probability of a hurricane, based on historical events, is two times greater in North Carolina, three times greater in Texas and almost six times greater in Florida than in the combined states of New Jersey, Pennsylvania, Delaware, Maryland, and Virginia, the region defined here as the Mid-Atlantic. We perform a simulation exercise in which the probability of a storm is increased to the levels in North Carolina, Florida, and Texas, holding other factors constant. This exercise provides a view of how a region like the Mid-Atlantic might develop differently under conditions expected with climate change.

We explore the implications of our amenity function and how it changes with distance to the coast through sensitivity analyses. The hedonic literature in economics finds that the magnitude of the capitalized value of coastal amenities in house prices is lower at greater distances from the coast (Bin et al., 2008; Conroy and Milosch, 2011; Major and Lusht, 2004). We analyze alternative specifications for the rate at which that decline occurs. This allows us to assess, again holding all other factors constant, including storm probabilities, how the type of coastal amenity affects housing and land market outcomes.

The model forms part of a growing literature on spatial urban growth ABMs (see Huang et al., 2014, for a review), which represent fine-grained, spatially heterogeneous processes and features such as localized sorting of households on the landscape. Studies with ABMs focused on coastal land use include Filatova et al. (2011a) and Filatova (2014), both of which incorporate flood risks and amenities in a model of location choice, and Filatova et al. (2011b), which uses an ABM without flood risks to analyze policies to protect open lands and ecosystem services. Each of these studies has contributed to the ABM literature on coastal land markets. Filatova (2014) shows how GIS data from a real landscape – a small town in North Carolina in their application – can be used to move ABMs to real-world settings. Filatova et al. (2011b) indicate how a spatial ABM can be used for policy analysis. Filatova et al. (2011a) show how a survey on costal residents' risk perceptions can be incorporated into an ABM.

We see three contributions of our model and its applications. First, it more fully integrates some important economic fundamentals than the existing literature. For example, the model formally specifies housing as a bundle of attributes that includes the coastal (spatial) amenity and incorporates that in consumers' utility functions. This recognition that spatial amenities (and disamenities) are part of the housing “bundle” is a long-standing feature of hedonic property value models (Rosen, 1974) and models of so-called “Tiebout sorting” (Tiebout, 1956; Kuminoff et al., 2013), in which households endogenously sort themselves into communities based on local amenities and taxes. This feature is important because it allows for feedback effects through land and housing prices – i.e., as spatial features change, either exogenously or due to policy levers, agents adjust, which changes prices and leads to further adjustments. The model here accounts for these feedbacks explicitly through the theoretical construct and simulation exercises. Second, our model also includes house size and lot size as housing attributes, which allows for analysis of the density of development across the landscape. This provides another test for the reasonableness of the results as economic theory says that where land is more valuable, density should be higher, all else equal. Finally, the scenarios and sensitivity analyses conducted with the model shed light on the relative contributions of amenities and storm costs in determining land market outcomes, an important application for design of land use policies in flood-prone areas.

The model is able to provide some sense of how U.S. policymakers can expect households to trade off the various factors that affect spatial patterns of development in coastal areas. It abstracts from ecological and geophysical features of the landscape and thus is not a model about system resilience in a coastal setting (Murray et al., 2013). However, it says more about economic drivers of development in coastal areas than most of the existing literature. Future studies that couple models of human and natural systems in coastal settings, including market prices, income, and agent optimizing behavior, will be important next steps (Murray et al., 2013; Lazarus et al., 2016).

2. Materials and methods

We describe our ABM below, beginning with the model's basic theoretical structure, followed by parameterization for our geographic setting. A full model description using the Overview, Design concepts, and Details + Decision-Making (ODD + D) format (Grimm et al., 2010; Müller et al., 2013) is provided in the supplementary materials.[2] The model is similar in spirit to our earlier model described in Magliocca et al. (2011, 2012, 2015), but it incorporates key features of a coastal

[1] There is a large literature analyzing consumer perceptions of hurricane risk, using both revealed preference methods (Carbone et al., 2006; Gallagher, 2014; Hallstrom and Kerry Smith, 2005) and surveys and hypothetical experiments (Baker et al., 2012; Dillon et al., 2011; Meyer et al., 2014; Peacock et al., 2005; and Siegrist and Gutscher, 2008).

[2] The ODD + D protocol is common practice for agent-based models. Our ODD + D document and model code are included on the OpenABM website, version/1/view" > https://www.openabm.org/model/5637/version/1/view.

landscape: amenities and expected storm costs associated with proximity to the shore. A unique feature of the model is its explicit accounting for both housing and land markets and the interactions between them, which permits analysis of the spatial patterns of development and also the density of development over the landscape. Moreover, while not a strictly economic equilibrium model in the spirit of Mills (1967), Muth (1969), and many economic models that followed, it has many of the features of those models: utility and profit maximization by agents, capitalization of landscape features in prices, and a sorting of consumers into houses on the landscape such that no one is better off by moving, given the options available to them.

2.1. A model of land and housing markets

The landscape is modeled at a 1-acre resolution and the full landscape covers 6400 acres (80 acres square, or 10 square miles). In each simulation period, land use and pricing decisions are made for each 1-acre cell. One side of the 10-square mile area is a coastline. Locations closer to the coast enjoy greater coastal amenities but also higher expected storm costs, as explained below. The landscape includes a central business district (CBD) with existing residential development at the start of the simulation periods, and a large area of undeveloped land that is gradually developed as population grows. The landscape is stylized and does not represent an actual region; it is parameterized (as explained in the next section) using information on agricultural land values, incomes, house prices, and other information from the Mid-Atlantic region of the U.S. thus the simulation outcomes are suggestive of development patterns in that region. Our objective is not to replicate any particular real-world outcomes but to explore the competing forces that guide the general patterns of residential development in a coastal setting and compare outcomes under alternative assumptions about storm frequencies and coastal amenities.

The model incorporates decisions made by three types of optimizing agents: heterogeneous consumers who purchase houses of various types, a representative developer, and farmer/landowners who choose between farming or selling their land to the developer. Consumers are heterogeneous in income and in preferences for the individual attributes of houses—house size, lot size, and coastal amenity. They take into account expected costs from storms and travel costs to the CBD, both of which vary by location. They maximize utility, choosing among available houses in each time period; interactions of consumers and the developer in the housing market result in market-clearing prices for each house type in each location. Those prices are then used by the developer to set price expectations for the next simulated time period for purposes of purchasing land for new development. Landowners use the value of their land in agriculture as a reservation price below which they will not enter the land market. Market-clearing prices for land result from interactions between the landowners and the developer. The profit-maximizing developer then builds new houses and sets asking prices based on land and other costs and the model continues to iterate through future periods. Fig. 1 shows a schematic of the model framework, including the time steps for each of the agent decisions and model outcomes.

We assume that consumers get utility from housing and a composite non-housing good, x. Each house i is characterized by its size, h_i, its lot size, l_i, and an amenity, $a(d_i)$, where d_i represents house i's distance from the coast. We assume that the utility function for each consumer has a Cobb-Douglas structure:

$$U = x^{\alpha} h_i^{\beta} l_i^{\gamma} a(d_i)^{\delta} \tag{1}$$

where $\alpha + \beta + \gamma + \delta = 1$.

A consumer has income, I, pays (annualized) price, P_i, for house i, and pays travel costs, ψ_i, which vary with distance to the CBD. Consumers also face expected costs from storms, which occur each year with probability, ρ. Based on this probability, consumers calculate the expected annual cost from storm damage as a percentage of the house's value. The model focuses on damage from flooding, which varies with distance from the ocean, $c(d_i)$, where $\partial c_i/\partial d_i < 0$, because storm surge-related flooding is typically greater in areas located closer to the shore. As explained in the introduction, we assume that consumers know the probability of a storm and the costs they will incur if a storm takes place. Although this information assumption is a strong one, incorporating uncertainty over risk perceptions introduces additional elements to the model that are outside our scope in this paper. Moreover, information about flood probabilities are available to the public from historical local experience and from Federal Emergency Management Agency (FEMA) Special Flood Hazard Area designations, which represent the one percent annual probability of a flood. We also abstract from considerations of insurance in order to isolate the competing influences of storm costs and amenities. Thus the budget constraint is given by:[3]

$$I = x + P_i(1 + \rho c(d_i)) + \psi_i \tag{2}$$

The Cobb-Douglas framework implies that at the utility maximum, the consumer spends a constant share of his income on housing. In our framework, this is given by the expression, $(I - \psi_i)\left(\frac{\beta + \gamma + \delta}{1 - \rho C(d_i)}\right)$. However, given the finite number of housing types, discrete time steps, and the inability to instantaneously adjust housing choices, consumers are not always able to obtain their globally optimal housing option. Thus the model calculates the utility level for each consumer for each available house given developer asking prices, and determines the consumer's most preferred house. It then calculates each consumer's bid price for each of the non-optimal alternatives that will yield the same utility as the preferred house. Consumers are only able to bid on houses for which their bids are greater than the developer's asking price. They also have a maximum share of income they are willing to pay for housing as defined by the maximization process above. The model then goes through an iterative matching process to allocate houses to consumers in each period.[4]

The model includes a representative developer who buys land from farmers and builds the number and types of houses in each period to maximize expected profits. [5] The developer is assumed to form price expectations for the housing market one year into the future and learn from past predictions relative to actual price outcomes.[6] He forms an expectation of the total housing demand in a given period based on observed population growth rates from past periods; that demand is then allocated to each housing type based on bids from past periods. Given the different lot sizes for each housing type, this provides a basis for translating expected housing demand into land demanded for new construction.

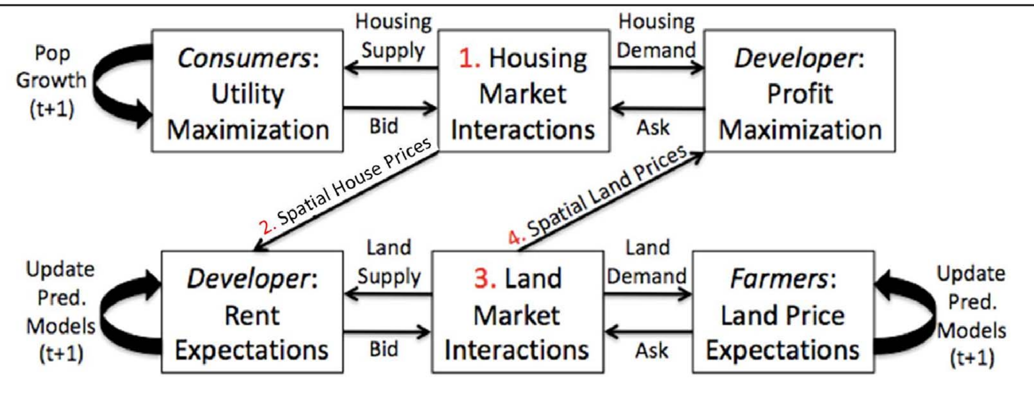
Undeveloped land is subdivided into 64 100-acre parcels (10 by 10 cells) that are regularly distributed across the landscape. When the developer buys land to build housing, we assume he must buy an entire allotment, i.e., farm. In each model period, a landowner decides whether to sell her farm to a developer or continue farming until the next period based on the expected return from selling relative to the value of the farm's agricultural return in perpetuity. Like the developer, landowners also form price expectations. If the expected price is above the

[3] In this notation, expected storm cost or risk, sometimes called average annual loss, is the value of the property exposed, P_i, multiplied by the probability of a storm, ρ, and the percent of the property damaged, which in our case varies by distance to the coast, $c(d_i)$. See Klijn et al. (2015) for discussion of risk and its relation to exposure.

[4] Each consumer is randomly assigned a residence time between 1 and 7 years; the model does not incorporate endogenous relocation. When a house is vacated, it goes back on the market thus each time period there are both newly built and resale houses available. More details are provided in the supplementary materials.

[5] The developer is a representative perfectly competitive agent and does not have monopoly power; given housing price forecasts, he bids for land an amount that results in zero profits. The assumption of a single developer simplifies the model.

[6] Details are provided in the supplementary materials. The price prediction models are based on techniques developed in Arthur (1994, 2006) and Axtell (2005).



Note: The numbers indicate the (counterclockwise) sequence of events within one simulated time period (t). Agents (*italics*) are labeled with the underlying conceptual model that governs their behavior. Intertemporal processes (t+1) shown include updating the developer's house price prediction models, updating the farmers' land price prediction models, and exogenous growth of the consumer population.

Fig. 1. Interactions among agents in the land and housing markets.

returns from agriculture, it represents a price floor for the landowner. The final sale price for land is a result of the interaction between the developer and landowners and is affected by the amount of competition in the marketplace.

Once land sales are finalized in each period, the developer builds houses in that period. Given the transaction price for land and expected return for each housing type, the developer constructs the housing type that maximizes profit for each 1-acre square cell on a cell-by-cell basis until the total expected demand for each housing type in the given time period is met.

2.2. Model parameterization

Fig. 2 shows the abstract geographic landscape in the model. The right-hand-side ("eastern" edge) of the region has the ocean, shown in blue on the map. The CBD, which has some development at the beginning of the model periods, is shown in the top, right-hand corner of the figure. Consumers are assumed to travel to the CBD for employment (as in other monocentric city urban economic models) and thus incur travel costs that include time and fuel costs. The remaining area is the initially undeveloped region. A single landowner/farmer agent owns each farm, and farms are homogeneous in their agricultural productivity; agricultural returns determine the reservation price for land sales.

The number of households entering the region is assumed to grow at 10 percent per year, and the model tracks growth over a 20-year simulation period.[7] The assumptions for farm size and productivity, transportation costs, and housing construction costs are shown in the Appendix, along with references. Table 1 shows parameter values for the household income distribution and the utility function. Incomes are distributed according to a log-normal distribution and range from \$40,000 for the lowest quintile to \$200,000 for the highest quintile. Income and consumer preference parameter values are randomly drawn for each model run from the ranges shown in Table 1, while the farmers' and the developer's price prediction models and the distribution and location of housing types in the CBD (which are used to initialize the model) are held constant across all runs. The degree of heterogeneity in preferences and income incorporated in the model is important as it will contribute to the observed sorting of households on the landscape.

Table 2 shows the coastal amenity function and storm parameters. We assume that the amenity value, a, is an exponentially declining function of distance from the coast: $a = A_0^{-rd}$ where r is the rate of decline and d is distance; A_0 is a constant term. The general shape of the amenity function is based on the hedonic property value literature that has assessed the value of ocean views and proximity (e.g., Benson et al., 1998; Major and Lusht, 2004; Gopalakrishnan et al., 2011; Bin et al., 2008). This literature generally finds that the capitalization of the coastal amenity in house prices falls off steeply with distance to the coast. We choose the parameter values for our amenity function such that the value of the amenity at the coast is double the value at the edge of what we define as the coastal region (the first ten columns of cells, or 0.4 miles, from the coast). In real world settings, the amenity function may vary significantly by characteristics of those settings. Sensitivity analyses on the amenity function parameters are conducted in section 3.3.[8]

The annual probability of a coastal storm or hurricane is also shown in the table. In the baseline case, it reflects the historical average probability in the Mid-Atlantic region; in the alternative scenarios, it reflects the probabilities in North Carolina, Florida, and Texas. This is a measure of the average probability in each region of any category (1–5) of hurricane in a given year (Costanza et al., 2008). The model does not distinguish among hurricanes of different intensities. The North Carolina, Florida, and Texas scenarios represent possible storm climates in the Mid-Atlantic region in the future with climate change. The consensus in the Fourth National Climate Assessment Report is that the worst hurricanes will increase in frequency though the precise estimates have great uncertainty (Kossin et al., 2017).

The storm costs in the model are parameterized using a three-step approach. First, we run the coastal flood module of the Hazus-MH model, a GIS-based model of damages from natural hazards developed for FEMA (FEMA, 2012; Scawthorn et al., 2006). The hydrology and hydraulics (H&H) model within HAZUS-MH uses a digital elevation model (DEM) to delineate the stream network in a region. We use a 30-meter DEM from the National Elevation Dataset maintained by the US

[7] Not all households may end up locating in the area as they are not guaranteed to find a house that they want and can afford. The model allows households to continue "looking" for a house for several time periods before assuming they locate elsewhere. In this sense, the model is what is often referred to as an "open city" model in the urban economics literature in that population size is endogenous (Pines and Sadka, 1986).

[8] The amenity value is treated as exogenous in the model; there are no feedbacks from housing development affecting the amenity, or other coastal ecological features. See Mills et al. (2016) for a model of sea level rise and urban growth that includes such feedbacks. That study does not model housing consumer decisionmaking but compares alternative adaptation strategies scenarios.

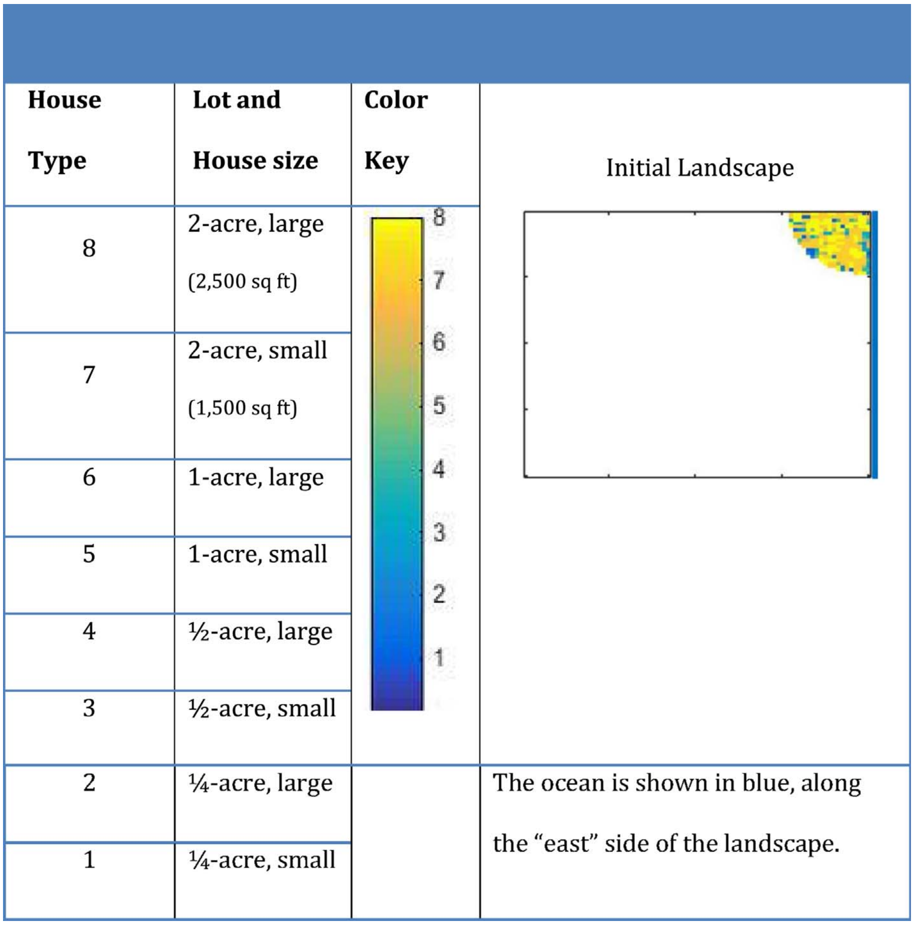


Fig. 2. Initial landscape and house types in the model.

Table 1
Model parameterization for utility function and household income.

Household income distribution[a]	
Income range	\$40,000–\$200,000
Low income range	\$40,000–\$59,999
Middle income range	\$60,000–\$99,999
High income range	\$100,000–\$200,000
Overall Mean (std. dev.)	\$86,493 (\$39,302)
Share of income on housing expenditure,[b] $ß + \gamma + \delta$	
Low-income consumers	0.35–0.42
Middle-income consumers	0.27–0.34
High-income consumers	0.18–0.26
Amenity preference parameter, δ	0.05–0.30

[a] Based on household incomes for suburban counties in the Mid-Atlantic region from the 2000 Census; household income is log-normally distributed.
[b] Safirova et al. (2006).

Table 2
Parameter values: Coastal amenity and storm costs.

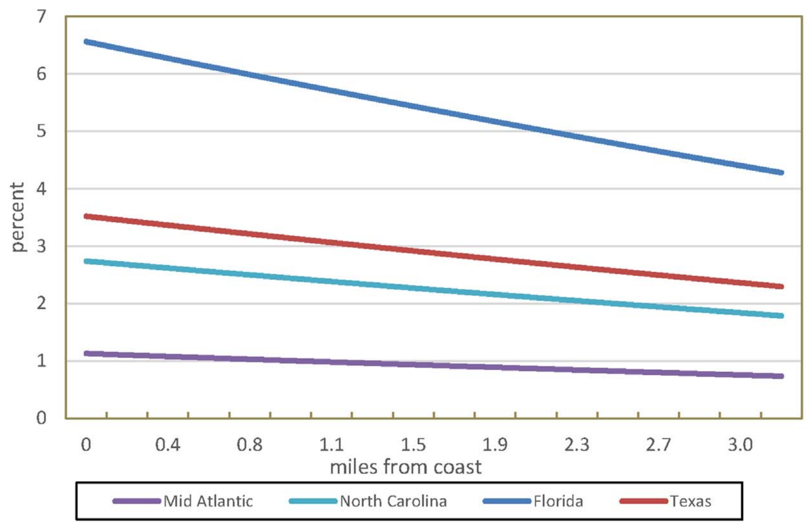
Coastal amenity, a (as a function of distance from coast, d)[a]	
$a = A_0 e^{-rd}$	Baseline case: $A_0 = 500{,}000;\ r = 0.08$
Probability of hurricane (any category, 1–5): [b]	
Mid-Atlantic (baseline)	0.123
North Carolina	0.298
Florida	0.714
Texas	0.383
Storm costs, c, as % of property value and as a function of distance from coast, d (in 1000s of ft.)[c]	
$c = c_0 + k_1 d + k_2 d^2$	$c_0 = 9.19;\ k_1 = -0.205;\ k_2 = 0.001$

[a] In the amenity sensitivity analyses in Section 5, we allow r to equal 0.06 and 0.10; d in this function is number of cells.
[b] From Costanza et al. (2008). This is the probability of a tropical storm or hurricane of any category (1–5) in any given year. Mid-Atlantic includes New Jersey, Pennsylvania, Delaware, Maryland and Virginia.
[c] Flood depths from 100-year flood based on coastal flood model results from Hazus-MH model (FEMA, 2012; Scawthorn et al., 2006) simulations for state of Maryland; depth-damage functions based on U.S. Army Corps of Engineers (2006); estimated coefficients (k_1 and k_2) result from regression of damages (as percentage of property value) on distance to coast (measured in 1,000s of feet) and distance squared. Property values from Maryland Department of Planning's MdProperty View data, http://planning.maryland.gov/OurProducts/PropertyMApProducts/PropertyMapProducts.shtml.

Geological Survey (USGS) for the state of Maryland (representative of the Mid-Atlantic region). The coastal module accounts for flooding due to wave run-up.[9] The model is run for a 100-year storm event and the output is flood inundation levels at a 30-meter resolution for that region.[10] Second, functions developed by the U.S. Army Corps of Engineers are used to calculate the percentage property value loss as a function of flood depths using residential property values in Maryland from the Maryland Department of Planning's MdProperty View dataset.[11] Finally, a regression of these percentage property losses on distance to the coast is estimated to establish a relationship between

[9] For a more complete discussion of the Hazus model, see Scawthorn et al. (2006).
[10] While the model can be run for multiple storm types, we choose the 100-year flood because 100-year floodplain maps are readily available in communities and are the basis for insurance requirements under the U.S. National Flood Insurance Program. Interestingly, flood depths in the 100-year flood roughly match the depths the model produces for Hurricane Isabel, which hit Maryland and surrounding states in 2003.

[11] For information on MdProperty View see http://planning.maryland.gov/OurProducts/PropertyMApProducts/PropertyMapProducts.shtml.



Note: expected damages are the probability of a storm multiplied by the damage (in % of property value) when a storm occurs.

Fig. 3. Expected property damage as percent of property value, alternative storm climate scenarios.

distance and flood damages.[12] The numbers in Table 1 show the estimated coefficients from this regression and make clear that the percentage property damage declines with distance to the coast, at a slightly decreasing rate.[13] Fig. 3 combines the storm probabilities and percentage storm damages and shows expected damages, as a percentage of property value, for each of the four storm climates we analyze—the baseline Mid-Atlantic case and the three scenarios we analyze in Section 3.2.

3. Results

We show the baseline model results first and in the following section, the results from our climate change scenarios in which storm costs increase. In section 3.3, we conduct sensitivity analyses on the amenity function.

3.1. Baseline model

Fig. 4 shows a map of development frequencies for the final time period in the model, $t = 30$, for the baseline Mid-Atlantic scenario. The colors show the average frequency of development, across all the model runs, for each cell on the landscape by the final model period.[14] The figure makes clear that development is more likely near the CBD and along the coast. In the first set of farms along the coast (the first ten columns of cells from the right-hand ("east") side of the map, or 0.4 miles from the coast), which we define as the coastal region, an average of 64 percent of the land area is developed by the final time period. We define the next 20 columns of cells (or next 0.8 miles) as the middle region; 32 percent of the land area in that region, on average, develops by the final period. Development in the remaining area on the map, the inland region, is much less common and some farms in that region never develop.

Fig. 5 shows similar information as Fig. 4 but highlights the housing types on the landscape for each of four time periods. The model is initialized over the first ten periods without population growth; Fig. 5 shows the results for the forecast periods 15, 20, 25, and 30. The maps in Fig. 4 represent average outcomes over the 30 runs of the model at each time step, and we shade only those cells that develop above a threshold frequency rather than all cells that develop in any model run. This is why a large area shows up as undeveloped in the maps; in the inland zone, the average probability of development across the runs is less than 4 percent, thus we consider those areas as undeveloped on average. [15] Within each developed cell, the housing type with the highest frequency of occurrence in the 30 model runs is shown on the maps.

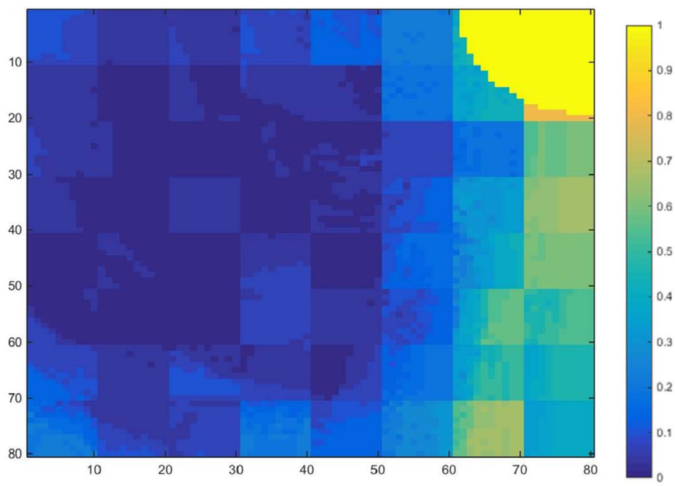
Several results are clear from Fig. 5. First, the coastal area and the area near the CBD develop first. This indicates consumers' desires to minimize travel costs and the value of the coastal amenity. Second, by the final period, the coastline has become fully built-out and the coastal region, which we define as the first 0.4 miles from the coastline, is almost fully developed. Third, by the 25th period, we begin to see some development outside of the coastal zone but it is next to the earlier development that has taken place, in what we define as the middle region, the next 0.8 miles. In other words, "leapfrog" development does not occur. This is different from spatial patterns in many ex-urban locations in the U.S., where leapfrog and patchwork development patterns are common, and different from results in the noncoastal ABM in Magliocca et al. (2012, 2015). The draw of the coastal amenity is likely the reason for this result, causing development to proceed inland from the coast over time in a relatively orderly way as households attempt to stay as close to the coast as they can. Fourth, the density of development is highest along the coast. We can see this from the housing types. The darkest blue colors represent types 1 and 2, which are the smallest lot sizes in our model—¼-acre and ½-acre lots. Denser development

[12] Flooding generally decreases with distance from the coast because of an increase in elevation in the landward direction (Brody et al., 2014). This is captured in the HAZUS-MH model; the estimated statistical relationship based on the HAZUS-MH results allows us to build the distance-damage relationship into our ABM.

[13] The estimated coefficients are statistically significant at the 1 percent level and the quadratic form shows a slightly better overall fit than a linear model.

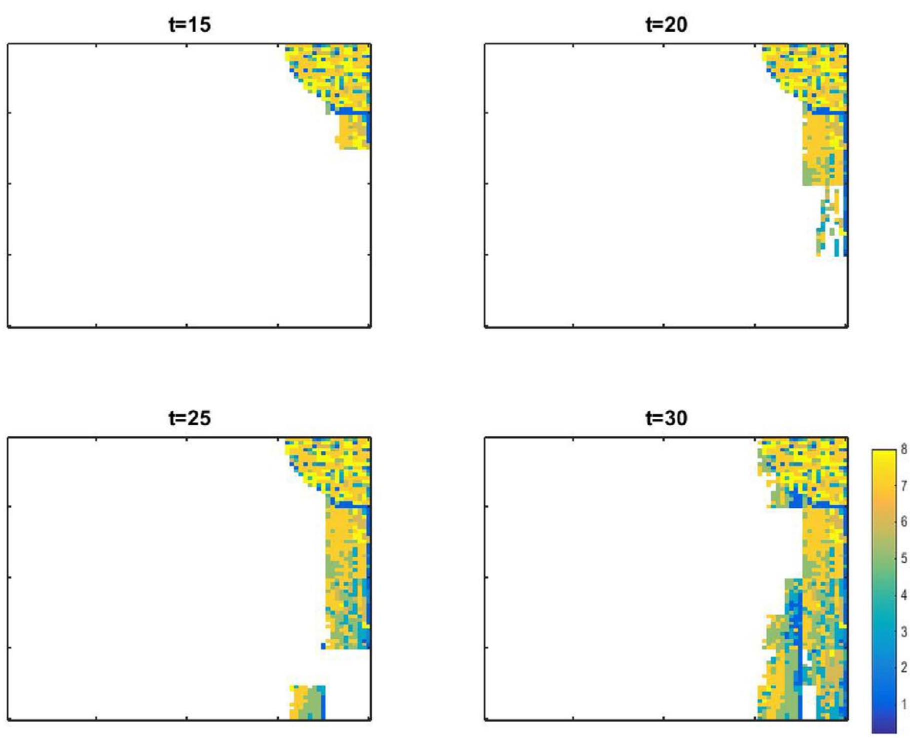
[14] The first ten time steps of each model run are used to spin-up agents' expectation models with 20 subsequent time steps of dynamic simulation. Each model scenario is repeated for 30 model runs to account for variation in model outcomes due to stochastic processes.

[15] The threshold we use is the overall average percent area developed across all 30 model runs. We select only the cells that develop most frequently, shading them until we reach the threshold. For example, if 50 percent of the area is developed at a particular time period, we color the cells that develop most often across the model runs until we reach the point that 50 percent of the total area is developed (Magliocca et al., 2011).



Note: Average frequency of development across model runs shown by color; see color key at right.

Fig. 4. Baseline model simulation results: Frequency of development across model runs.



Note: housing types 1-8 shown by colors; see color key at lower right.

Fig. 5. Baseline model simulation results.

along the coast is consistent with higher-valued land; as Fig. 6 shows, the average per-acre land price, across all of the model runs, for each of the 64 farms tends to decline with distance to the coast.

Table 3 provides further information on land prices, as well as weighted (by type) average house prices and average household income by coastal, middle and inland regions; 95 percent confidence intervals are also shown. Land and house prices are highest in the coastal region. Land prices show the biggest differences: the average price in the coastal region is 2.4 times the average in the middle region and 3.2 times the average inland price. Average house prices in the coastal region are 1.2 times the average house price in the middle and 1.4 times the inland price. There are two reasons why the difference in average house prices across regions is less than the difference in average land prices. First, house prices reflect both locational factors and the house types as the developer and consumers interact in the marketplace to reach a balance between preferences for particular house types and locations, on the one hand, and ability and willingness to pay on the other. This sometimes leads to house types that are smaller or have smaller lots and are thus less expensive, offsetting the higher price consumers are willing to pay along the coast. Second, as long established in urban economics (Alonso, 1964), because land is fixed in supply, land values tend to capitalize locational amenities (or

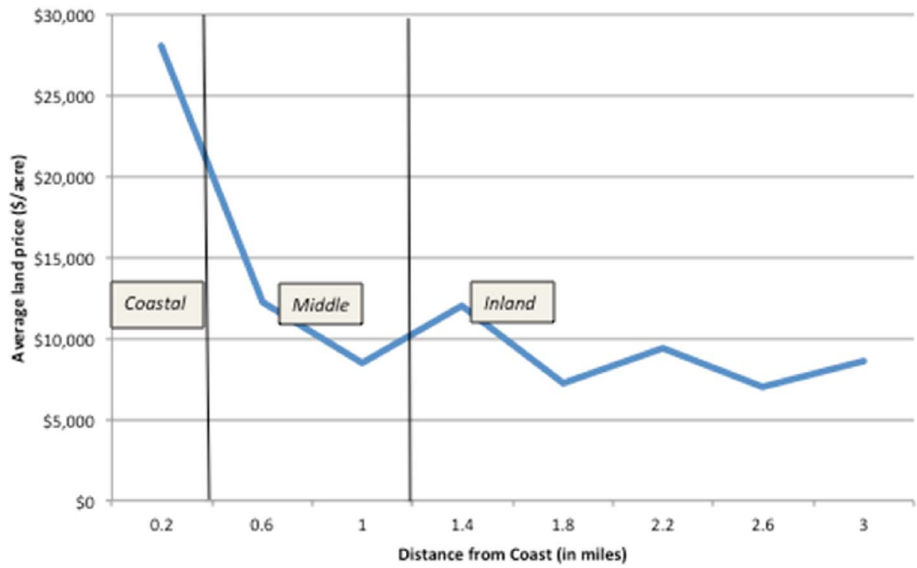


Fig. 6. Average land prices by distance to coast, baseline scenario.

Table 3
Mean and 95 percent confidence intervals: Land prices, house prices, and incomes by region, baseline case.

	Land Price ($/acre)	Annualized House Price	Household Income
Coastal	$27,970 ($27,634 – $28,306)	$16,483 ($16,173 – $16,808)	$122,591 ($121,980 – $123,210)
Middle	$11,795 ($11,672 – $11,919)	$12,922 ($12,592 – $13,256)	$99,800 ($99,310 – $100,290)
Inland	$8820 ($8696 – $8943)	$5074 ($3337 – $6976)	$83,960 ($83,100 – $84,820)

Note: confidence intervals in parentheses.

disamenities). We see a steep fall in land prices especially from the coast to the middle region, reflecting the steeply non-linear amenities function (see Table 2). Also, it is notable that the regions are clearly distinguished from each other in that the 95 percent confidence intervals for land and house prices and income do not overlap.

Average household incomes are significantly higher in the coastal region than in the other two regions, and the 95 percent confidence intervals do not overlap, which provides our first evidence of sorting on the landscape. All consumers get utility from the coastal amenity, but consumers are heterogeneous in incomes and higher income consumers have the ability to outbid those with lower incomes for the ability to live near the coast. Consumers are also heterogeneous in preferences and we find that the mean coastal preference parameter, δ, for consumers who locate in the coastal region is nearly twice as high (0.1231) as the mean of those in the inland region (0.0684). Thus consumers with strong preferences for the coast end up living closest to the coast.

In these baseline simulations, the value of the coastal amenity seems to outweigh the risks of damages from coastal storms. As the population grows, the coastal region develops first and has the highest average land and housing prices; in addition, higher income households tend to live in the coastal region. These results are intuitive and seem to be consistent with coastal development patterns in the U.S. and elsewhere. The question we raise then is whether an increase in expected storm costs, all else equal, could change these outcomes. Current scientific consensus is that climate change will lead to an increase in the frequency of the worst hurricanes (Category 4 and 5), though there remains a good deal of uncertainty in the forecasts (Melillo et al., 2014). We analyze potential climate change scenarios in the next section.

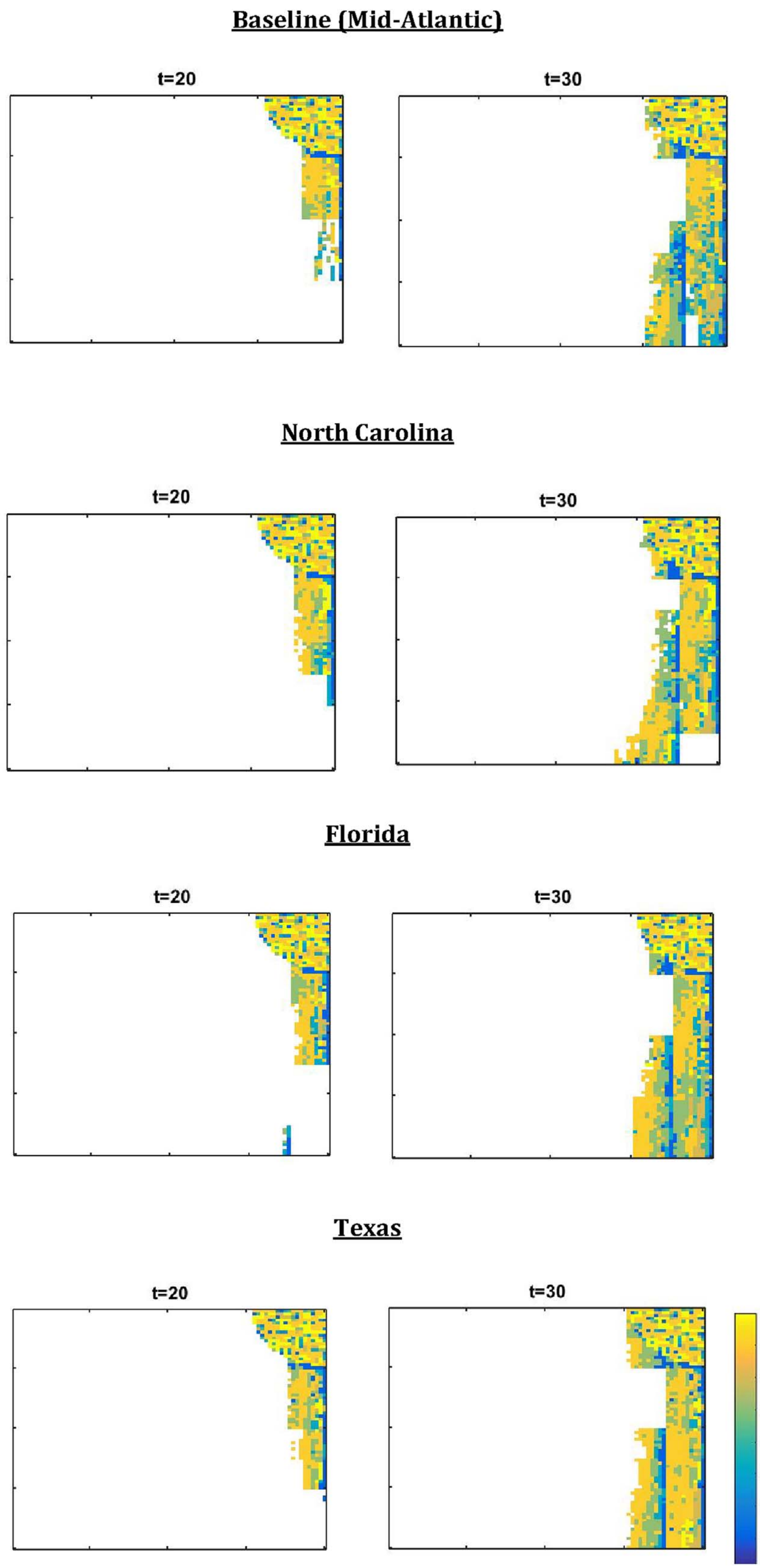
3.2. Climate change scenarios: higher probabilities of coastal storms

The baseline results assume an annual storm probability of 0.123, equal to the historical average for the Mid-Atlantic region. We rerun the model assuming the probability is equal to the historical averages for North Carolina (0.298), Florida (0.714), and Texas (0.383) (Costanza et al., 2008). We leave the remaining parameters of the model the same, including the amenity values. We also assume the damage function stays the same (Table 2)—i.e., expected storm costs are higher because the likelihood of a storm increases and possibly because house values change, but the relationship between the percent of property value damaged and flood depths stays the same. While the precise increase that would result from climate change, and when it would occur, is highly uncertain, these results provide a sense of whether and how housing and land markets might capitalize this change in risks if agents are fully informed and rational. The expected damages as a percentage of property value by storm scenario and distance from the coast are shown in Fig. 3 above.

Fig. 7 shows the spatial patterns of development and housing types in these alternative scenarios, along with the baseline for comparison; to economize on space, we show only the results for $t = 20$ and 30.[16] Development occurs first near the CBD and along the coast before any inland development occurs in all four scenarios. A small amount of development begins to occur away from the coast, and before the coast is completely developed, by period 20 in the Florida scenario and by period 25 (not shown in the figure) in all of the others. However, in almost all of the scenarios, the coastal region as we've defined it (the first 0.4 miles, or 10 cells, inland from the coast), is fully developed by the final period.

There is a small shift in housing types across the scenarios. While smaller lot sizes lie along the coast in all four scenarios, consistent with higher-priced land in those locations, the highest storm risk cases (Florida and Texas) show slightly more of the larger lot types in the coastal region than the other two scenarios. In the Texas scenario, for example, 41.3 percent of the houses have 1- and 2-acre lots (house types 5, 6, 7, and 8) in the coastal region; 37.3 percent have 1- and 2-

[16] We omit the development frequency maps for the alternative storm scenarios also to economize on space and because they show strong similarities to Fig. 4—i.e., the coastal region develops in a high percentage of model runs and the inland region develops in almost no runs. One interesting difference is that the area near the CBD has a slightly higher frequency of development in the three high storm scenarios than in the baseline and coastal areas farther "south" have a somewhat lower frequency than the baseline.



Note: Housing types 1-8 shown by colors; see color key in Figure 4. Coastline is along the right-hand vertical axis of each map, i.e., the "east" side, and CBD is in the upper right corner.

Fig. 7. Alternative storm scenario simulation results: Spatial development patterns and housing types.

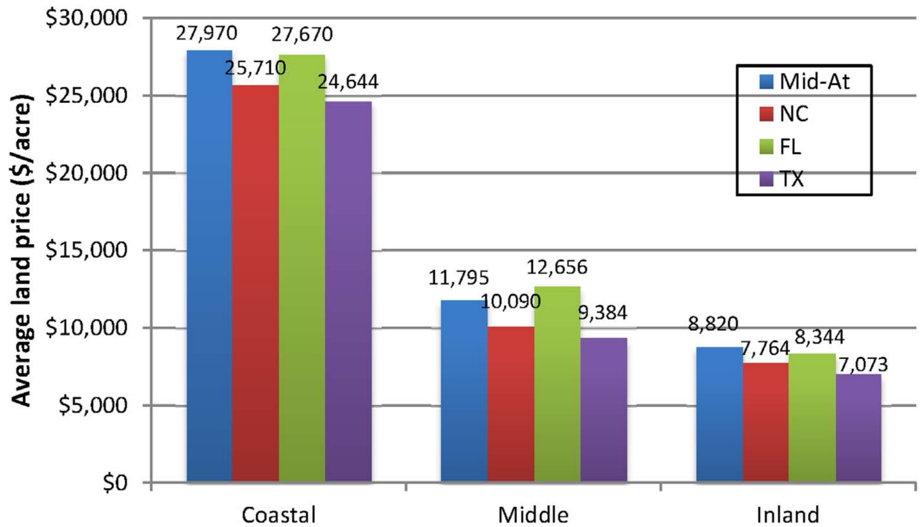


Fig. 8. Average land prices, by storm scenario and region.

acre lots in the baseline case. These results are associated with lower average land prices in the high storm scenarios, as shown in Fig. 8. The higher storm risks appear to be capitalized into land values—the average price in the coastal region is lower in each of the high storm risk scenarios than in the baseline case. The effect is relatively small in the Florida scenario, which has an average price only 1.1 percent lower than the baseline, but it is larger in the other two scenarios—8.1 percent and 11.9 percent lower in the North Carolina and Texas cases, respectively, than in the baseline.[17]

Average house prices differ little across the four scenarios. The Florida scenario shows the lowest average coastal price but it is only 1.3 percent below the price in the baseline case. This reflects the multiple margins over which consumers can adjust their housing demand as houses are characterized by their location, lot size, and house size, coupled with the heterogeneity of consumers in the market. With higher storm costs, demand shifts away from the coastal amenity attribute of housing toward the other two attributes, lot size and house size; as these shifts occur, the impact on house prices is muted, particularly compared to the impact on land prices.

Average incomes in the coastal region are 1.3–2.7 percent lower in the high storm cost cases compared to the baseline. In the inland region, average incomes are 1.2–2 percent higher. Thus we find that, while the differences are not large, consumers sort themselves differently on the landscape as storm risks change. The higher storm costs reduce demand for coastal locations by some consumers, which reduces land prices and makes those locations relatively more affordable to others who have less income.

Taking the simulation results as a whole, we see that increasing the probability of a hurricane ends up having only a small impact on the spatial patterns and overall extent of development. There is some resorting of households on the landscape, but the final outcomes—in terms of development patterns—look very similar across storm scenarios.

The outcomes may result, in part, from the fact that the expected damages from storms, even in the Florida scenario, are not particularly high. There are significant differences in the magnitude of the expected damages across scenarios, but very little difference in total housing costs (including expected damages) as a fraction of income for most households. We show this with some numerical examples in Table 4. The table shows the average expected annual property damage and average total housing costs (excluding transportation costs) as a percent of income in each of the three landscape regions for two storm climate scenarios. Total housing costs include the average house price and the expected storm damages. Although the differences in expected property damages between the two storm scenarios are relatively large, they contribute to only a small difference in total housing costs as a fraction of income. For example, in the coastal region, housing costs are 13.6 percent of income for an average household in the coastal region in the baseline Mid-Atlantic case and 14.6 percent in the Florida case.[18]

We note that our damage function is based on flood modeling in FEMA's Hazus flood model and an estimated statistical relationship between damages (as a percent of property value) and distance to the coast; that relationship remains the same across the storm scenarios, with only the probability of a storm changing.[19] If the damage function – i.e., the relationship between flood depths and damages – is significantly altered by climate change, we may see larger differences across the scenarios.

The more important factor, however, may be the amenity value. Our results so far suggest that the amenity seems to be valuable enough for many households such that it dominates the expected storm costs. We explore the amenity function in the next section and how differences in it may alter housing choices and resulting spatial patterns of development.

3.3. Sensitivity analyses: coastal amenity values

The amenity value follows an exponential decline function; in the baseline case, the rate of decline is 0.08 (see Table 2). There is strong evidence that consumers perceive amenities as declining with distance from the coast, but the rate of decline may differ depending on physical features of the coast, including topography that may affect views, and on the degree of accessibility. In the two alternatives explored in this section of the paper, we change the rate of decay of the amenity to assess the sensitivity of our results to the amenity specification. We vary the rates from 0.06 to 0.10. In all cases the amenity has its greatest value at the coast but in the first sensitivity case (0.06), the value stays higher as one moves away from the coast (i.e., the amenity function has a flatter slope) whereas in the second (0.10), the value drops off more

[17] Although the largest reduction would be expected for the Florida case because it has the highest probability of a storm, there are many factors that come into play, across multiple model runs, in determining land prices, including the timing of land sales; the averages across runs and time periods mask many of these factors.

[18] Though not shown in the table, the results for the other storm scenarios are similar.

[19] Only the function stays the same, but total expected damages will increase because the probability increases. Moreover, as housing types and values change, this will affect total damages as well.

Table 4
Expected annual storm costs and housing costs as percent of income.

	Coastal		Middle		Inland	
	Mid-Atlantic	Florida	Mid-Atlantic	Florida	Mid-Atlantic	Florida
Average annual expected property damage	$182	$1049	$130	$758	$87	$529
Average annual housing costs as % of income[a]	13.6	14.6	13.1	13.8	12.5	13.3

[a] Housing costs are the sum of annualized house price and expected annual storm damage costs.

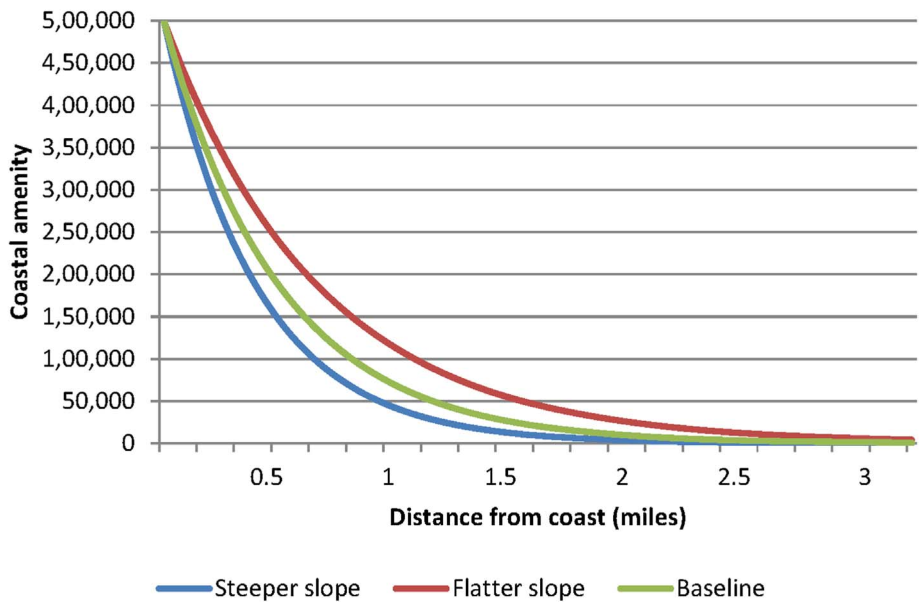


Fig. 9. Coastal amenity function: Baseline and sensitivity cases.

quickly (i.e., the function has a steeper slope). The three functions are shown in Fig. 9.

One situation that could explain these scenarios is public beach access where the flatter slope represents a region with more extensive or easier access. Another possibility may be ocean views, with the flatter slope representing a situation in which properties farther from the coast retain some views. We assume the value directly at the coast is the same in all three scenarios; we vary only the rate of decline. It is important to point out, however, that changing the slope changes the magnitude of the amenity throughout the landscape. A steeper slope reduces the magnitude and a flatter slope increases it. Thus our sensitivity cases have altered both the relative (across the coastal, middle, and inland regions) and absolute values of the amenity.

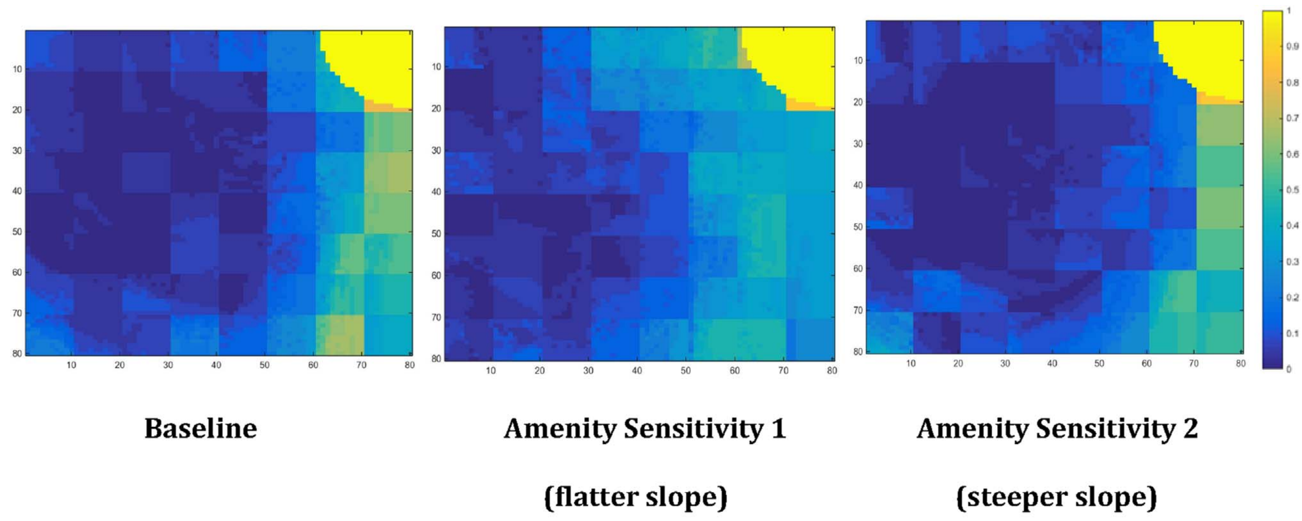
Fig. 10 shows the average frequency of development across the landscape by $t = 30$ for each of the sensitivity cases as well as the baseline (reprinted from Fig. 3). Some differences show up across the three scenarios, particularly for the coastal region. The likelihood of land in that region developing (indicated by the colors on the figure) is less in the first sensitivity case (flatter slope) than in the second (steeper slope), with the baseline case lying in between. By $t = 30$, an average of 64 percent of the land area in the coastal zone is developed in the baseline case; in the two amenity sensitivity cases, 49 percent (flatter slope) and 65 percent (steeper slope) of coastal land area is developed on average. The figure also shows that the likelihood of noncoastal (middle and inland region) development is higher when the amenity slope is flatter and lower when it is steeper. By $t = 30$, we find that 32 percent of the land in the middle zone is developed, on average, in the baseline case, whereas 41 percent is developed when the amenity slope is flatter and only 23 percent when it is steeper.

Fig. 11 shows the housing types at $t = 20$ and the final period, $t = 30$, for the three scenarios (reprinting the baseline maps from Fig. 4).[20] It is still the case that development starts near the CBD and along the coastline near the CBD in all three scenarios. But in the first sensitivity case, development takes place in the middle region by $t = 20$, before the coastal region is fully built out. By the final period, the coastal region is relatively developed but there is far more development in the middle region than in the baseline case. In amenity sensitivity 2 (steeper slope), all development is in the coastal region.

Table 5 shows the percentage of total development in each region by the final period under the two amenity sensitivities and the baseline; the Texas storm scenario case (with baseline amenity slope) is also shown for comparison. In terms of land area, the coastal region accounts for 12.5 percent of the entire land area; the middle and inland zones account for 25 and 62.5 percent of the land area, respectively. The table shows that in all four scenarios, housing development is proportionally greater in the coastal region than the land area available in that region. In the baseline case, 44.5 percent of all development that occurs by the final period is located in the coastal region. When the amenity slope is flatter, this percentage falls to 32 percent; when it is steeper, it rises to 57.3 percent.

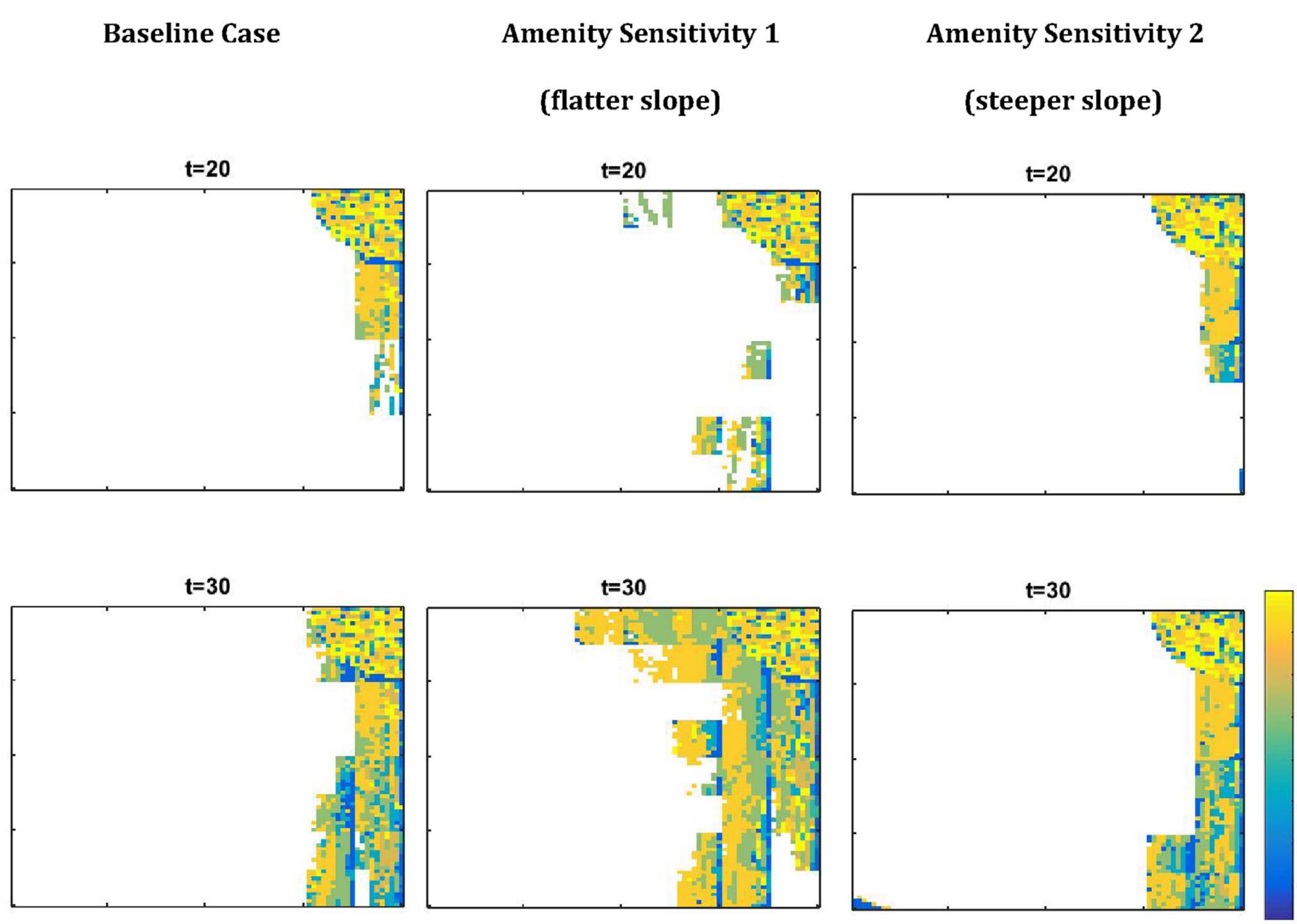
The patterns in Figs. 10 and 11 and Table 5 are as expected: because a flatter slope indicates that the coastal amenity holds its value relatively more throughout the modeled geographic area and a steeper slope indicates that it falls off more quickly, we see development shifting inland to a greater degree in the first case and staying near the coast in the second. The table also provides more evidence for our earlier statements that greater storm risks have little effect on the spatial patterns of development: in the high storm costs case (the Texas scenario is shown for comparison but the others exhibit similar

[20] The housing type maps are again drawn using the threshold method described in Section 3.1 above.



Note: Probability of development shown by color; color key at right.

Fig. 10. Baseline and amenity sensitivity simulation results: Probability of development.



Note: Housing types 1-8 shown by colors; see color key at right. In all cases, the storm scenario is the baseline, Mid-Atlantic case.

Fig. 11. Alternative amenity scenario simulation results: Spatial patterns of development and housing types.

Table 5
Percentage of land area and housing development by region and scenario.

	Coastal	Middle	Inland	Total
Total Land Area	12.5	25.0	62.5	100.0
Developed Land Area				100.0
Baseline	44.5	43.0	12.5	100.0
Flatter Amenity Slope[a]	29.2	46.6	24.1	100.0
Steeper Amenity Slope[a]	51.1	34.9	14.0	100.0
High Storm Risks (Texas)	46.5	41.3	12.2	100.0

[a] The coastal amenity decreases with distance from the coast; a flatter (steeper) amenity slope means this decrease is smaller (larger) than in the baseline case.

patterns), there is very little difference from the baseline in the percentage of development allocated to the three regions.

While the different amenity slopes lead to different spatial patterns of development, they also alter the overall amount of development. As explained above, the steeper slope lowers the value of the amenity throughout the landscape (except directly at the coast) and the flatter slope raises it. Because we have an open city model, in which housing consumers can choose to enter and exit, there is more total development by the final period when the amenity function has a flatter slope—17 percent increase over the baseline case—and less when the function has a steeper slope—11 percent decrease over the baseline. And the consumers who locate in the area in the flatter slope case—-regardless of which of the three regions they are in—have the highest average coastal amenity preferences of the three scenarios.

Changes in the coastal amenity have a greater impact on the spatial patterns of development than changes in the probability of a storm. We took a reasonable approach to specifying the amenity—it is a hedonic attribute of housing that varies by location with locations closer to the coast having higher values. This is consistent with findings in the empirical literature. Nonetheless, the amenity is not a product directly traded in markets with an established market price, thus there is no way to validate specific values with real-world data. What our simulation exercises do is provide some information about how one type of change to the amenity function can affect land and housing market outcomes, which allows us to compare the relative influences of the amenity and the storm risks. The results suggest that, holding all else constant, the amenity matters and has a significant effect on development patterns in a coastal area. This means that as climate change increases hurricane risks, we can expect responses by residents to differ across coastal areas depending on the countervailing positive influences of living in those areas.

4. Discussion

An important component of improving resiliency in the face of climate change will be a relocation of people and property away from the riskiest areas. This is particularly true in some coastal settings. However, the pull of coastal amenities, for many households, may counterbalance the push from expected storm costs. This may have been one factor in the lower than expected uptake of buyouts of damaged properties in New York after Hurricane Sandy in 2012. Even though the state offered to pay 100 percent of pre-storm market value for damaged properties, and an additional 5 percent bonus on homes in particularly risky areas, only an estimated 10 to 15 percent of eligible homeowners accepted the buyout offers (Kaplan, 2013; Chaban, 2015).

The results of our simulations indicate that outcomes like these may result simply from the strong attraction of coastal amenities. Our simulation model abstracts from insurance and assumes coastal residents fully understand storm risks and incorporate them in their decision-making. Even in this stylized setting, we find that coastal areas in our model see substantial development. Thus while relocation may be difficult because of subsidized rates in the National Flood Insurance Program (Michel-Kerjan and Kunreuther, 2011), or because many coastal residents are poorly informed or behave in ways contrary to the standard expected utility maximization framework (Botzen et al., 2015; Dillon et al., 2011), our model suggests that it may not even be these factors that cause the problems. People like living near the coast and the nature of that amenity may be the key factor explaining the spatial patterns of development in many locations.

Our simulations with higher storm risks show very little change in the spatial and dynamic patterns of development. In all storm climate scenarios, including the baseline Mid-Atlantic case and the higher storm probability scenarios, the areas along the shoreline are developed first. By the end of the simulated time periods (20 periods), the coastal region is almost fully built out in the baseline case and in two of the high storm scenarios; in the other high storm risk scenario, it is still highly developed but slightly less so. Thus, even with the probability of a hurricane up to six times greater than the current level in the Mid-Atlantic region, we do not see markedly less coastal development.

Where we do see differences is in the sorting of households on the landscape. In the higher storm risk scenarios, incomes of households who locate in the coastal zone are 1.5–3 percent lower, on average, than in the baseline case. These lower incomes are associated with lower land prices. Average land prices in the coastal region are 1, 8, and 12 percent lower in the three high storm risk scenarios than in the baseline Mid-Atlantic scenario. Thus, as would be predicted by economic theory, storm risks are capitalized in land prices. Coastal amenities are also capitalized in land prices: average prices in the coastal zone in all scenarios are significantly higher than in the inland areas. These higher land prices in the coastal region indicate that the amenity is outweighing the risks in all of the storm scenarios we analyze, an outcome that rings true for most coastal regions around the U.S. In all scenarios, households with relatively high coastal amenity preferences locate on the coast.

This resorting of households on the landscape based on income and preferences highlights another problem that policymakers will face with climate change. As coastal residents begin to understand the impacts of climate change and market outcomes begin to reflect that understanding, it may be the lowest income households left in the most vulnerable positions. Policymakers will need to understand how any policies and programs they design for relocation affect both efficiency and equity outcomes.

Future research that examines how misperception of risks might affect coastal land use patterns would be a useful extension of our analysis, as would an analysis of insurance. In addition, analysis and comparison of the effectiveness of policies to both increase insurance uptake and alter location patterns in a way to reduce exposure to storms would be worthwhile.

5. Conclusion

In this paper, we develop a dynamic, spatial simulation model of housing and land use in a coastal area and use it to evaluate how the competing influences of amenities and storm risks affect spatial patterns of development, housing types, and house and land prices. In the model, housing consumers are assumed to understand and incorporate storm risks in their decision-making. We thus abstract from issues related to misperceptions of risk, decision-making based on heuristics, and a number of other behavioral considerations to assess whether the utility enjoyed from higher levels of coastal amenities can outweigh concerns over storm damages. We use the model to assess how outcomes change if storm risks increase with climate change and how characterization of the coastal amenity affects outcomes. The advantage of the stylized model is that it can be used to isolate the competing influences of amenities and storm risks in the absence of real-world complicating factors such as landscape features, local zoning regulations, and other factors. This allows us to gain an understanding of the degree to which coastal amenities tend to offset expected storm costs. In addition, the economic characteristics of the model take account of the

many interactions and adjustments in land and housing markets over time.

Our main result is that significantly increasing the probability of a hurricane does little to change the spatial patterns of development. Our model is parameterized to the Mid-Atlantic region of the U.S., where the probability of a hurricane is low. If that probability increases to match levels in Florida or other high-risk regions, all else equal, we continue to see the coastal region fully developing out over time. However, there is a resorting of households on the landscape: average land prices in the coastal region fall as storm risks rise and this leads to a decline in average household incomes in that region.

The coastal amenity appears to affect location patterns more than storm risks. When we alter the amenity, keeping storm risks at the baseline, Mid-Atlantic level, we see bigger changes in the spatial pattern of development. This suggests that regions may experience different responses to the risks from climate change based not just on the level of those risks but also on other features of the coastal environment.

Simulation of decision-making processes helps to understand potential adaptive responses by the various actors—housing consumers, developers, and landowners—that drive coastal development. Findings from our model experiments highlight the importance of heterogeneity among residential housing consumers. Even when some or most consumers consider locations along the coast too risky and/or expensive, there is likely to be a sufficient number with differing perceptions, preferences, and incomes such that development pressures along the coast continue.

We see three main take-away from our research. First, even if coastal storm risks increase dramatically with climate change, there is little evidence that development along the coast will be reduced as a result of market forces alone. Our alternative storm scenarios for the Mid-Atlantic region were designed to mimic the storm frequencies currently seen in states such as Florida, North Carolina, and Texas, and we find that those changes would have very little effect on the overall amount of coastal development. Second, even though the amount of development remains relatively unchanged, households are sorted differently by income and preferences on the landscape. We find that when storms occur at greater frequency, the average incomes of households living near the coast are lower. This leads to our third take-away: both amenities and storm risks are capitalized in land values; as storm risks increase, all else equal, land prices in riskier areas tend to fall, making those areas more affordable. All of these market shifts highlight the difficulty policymakers face in trying to alter development patterns in private land and housing markets to reduce storm costs.

Funding

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Acknowledgements

We appreciate the helpful research assistance of Ziyan Chu.

Appendix

Table A1 shows some of the parameters used for the baseline model (in addition to the parameters of the utility function shown in Table 1 and storm and amenity parameters in Table 2). The first several rows show baseline assumptions for the farm size and productivity distributions, which are based on data from farms in the Mid-Atlantic region of the U.S. The costs of housing construction include the house construction costs and associated infrastructure costs, such as streets and sewers or septic systems. We use an average of construction costs in urban areas of the Mid-Atlantic region, with a range of \$85 to \$165 per square foot (U.S. Census Bureau, 2008). Infrastructure cost estimates are derived from Frank (1989), Fodor (1997), and more recent evidence from Juntunen and Knaap (2011). Travel costs to the CBD assume time costs of \$1.30/mile, and monetary costs of \$0.54/mile (U.S. Bureau of Transportation Statistics, 2007).

Table A1
Model parameterization: farms, development costs, and transportation costs

Number of farms	64
Mean (std. dev.) farm size, in acres[a]	100 (0)
Mean (std. dev.) agricultural return, in \$/acre[a,b]	\$2486 (\$0)
Housing construction cost per square foot[c]	\$85–\$165
Infrastructure cost per housing unit[d]	
1-acre lots or smaller	\$10,000–\$20,000
2-acre lots	\$23,000
Transportation costs (\$/mile)[e]	
Time	\$1.30
Out of pocket	\$0.54

[a] Data from The Census of Agriculture (U.S. Department of Agriculture, 2007).
[b] Agricultural return is the discounted net present value of average farm income divided by total farm acreage for Mid-Atlantic states (Delaware, Maryland, Pennsylvania, and Virginia).
[c] U.S. Census Bureau Manufacturing, Mining and Construction Statistics. http://www.census.gov/const/charindex.html#singlecomplete.
[d] From Frank (1989), Fodor (1997), Juntunen and Knaap (2011).
[e] Safirova et al. (2006). Calculations in that study based on U.S. Bureau of Labor Statistics' Consumer Expenditure Survey.

Appendix B. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.ocecoaman.2018.01.021.

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